A Case-Based Assistant for Clinical Psychiatry Expertise.

Isabelle Bichindaritz

Université René Descartes
UFR de mathématiques et informatique
LIAP-5
45 rue des Saints-pères
75006 Paris, France
tél : (+33) 1 44 55 35 63
email : bici@math-info.univ-paris5.fr

Université René Descartes
Faculté de Médecine Cochin-Port Royal
Hôpital Sainte-Anne, CMME
service of professor Samuel-Lajeunesse
100 rue de la santé
75014 Paris, France

Abstract. *Case-based reasoning is an artificial intelligence methodology for the processing of empirical knowledge. Recent case-based reasoning systems also use theoretic knowledge about the domain to constrain the case-based reasoning. The organization of the memory is the key issue in case-based reasoning. The case-based assistant presented here has two structures in memory : cases and concepts. These memory structures permit it to be as skilled in problem-solving tasks, such as diagnosis and treatment planning, as in interpretive tasks, such as clinical research. A prototype applied to clinical work about eating disorders in psychiatry, reasoning from the alimentary questionnaires of these patients, is presented as an example of the system abilities.*

1 INTRODUCTION

Case-based reasoning proposes an artificial intelligence methodology for the processing of empirical knowledge. By definition, a case is a set of empirical data. It may often be presented to the system as an instance of a certain type or concept, in problem-solving as well as in classification. The mainspring of case-based reasoning is to use one or several already met cases to process a new case. The processing of a new case may belong to an analysis task, such as solving a diagnostic problem [1] or planning [2], or to a synthesis task, such as concept learning [3].

A case-based reasoning system uses a knowledge-base containing a set of previously met cases, which is enriched each time a new case is processed. The case knowledge-base is similar to a memory. Reasoning involves organizing this memory to make possible the comparison of a new case with the numerous memorized cases. An indexed memory is partitioned by means of indexes, which are the elements of the cases representation retained as significant regarding the task to realize.

Moreover, case-based reasoning systems permit to build knowledge-bases automatically by case-based learning. This learning process may be conducted through the guidance of an expert, such as in [1], or unsupervised.

In the system presented here, the memory structures are twofold. First, cases represent specific, contextualized experiences, and second concepts represent general knowledge. The problem of the evolution of the structures from the accumulation of numerous cases to the incremental concept learning is the key problem addressed in this paper. This memory organization gives the system the ability to perform, in a unified framework, analytic tasks, such as diagnosis or treatment planning, and synthesis tasks such as assistance to clinical research.

The motivation for this work is that clinical expertise is not uniform. On the contrary, it assumes, for the same clinician, many skills, such as diagnosis, therapy and research.. So these facets must not be conceived as separated, but as the result of the growth, thru experience, of a unique competence, presented here as the discerning organization of the memory.

The second section presents important issues in case-based reasoning, such as its emergence and its evolution. The third section studies the case-based reasoning tasks addressed here. The fourth section deals with the memory organization. The fifth section proposes the example of a prototype for the system that studies the alimentary questionnaires of eating disordered patients. Finally, the sixth section brings out the conclusion.

2 CASE-BASED REASONING EVOLUTION

2.1 Emergence

The original research on case-based reasoning emerged from work in natural language understanding. Schank proposed a knowledge representation, scripts [4], and a memory organization, memory-organization packets or MOPs [5], allowing to known parts of the texts to understand to be efficiently retrieved. Later, the organization of the knowledge in a structured network, with high-level and low-level knowledge, appeared, jointly with the ability to learn. The design of memories to learn, such as GBM [6], aimed at the acquisition of knowledge from textual data, and were implementations as faithful as possible to the theory of dynamic memory [5]. They were followed by the first case-based reasoning systems, and progressively applied to the various tasks they presently cover.

2.2 Evolution

Later, researchers in case-based reasoning realized the importance of using a model of the domain to constrain the reasoning process. Some researchers proposed that ossified cases and paradigmatic cases should be integrated to the memory [7]. Others used case-based reasoning to short-cut a causal model of heart-failure disease [8]. Yet others used a causal physio-pathological model to constrain the case-based reasoning [9]. This model simulates the expert's reasoning, and is a heuristic guiding the case-based reasoning, which is the central process performed by the system. Case-based and model-based reasoning systems complement each other well, partly because of the type of knowledge representation they share : large chunks of knowledge rather than fragmented parts as rule-based reasoning systems [10].

In weak-theory domains, such as psychiatry, case-based reasoning is a main reasoning, and can give results where model-based and rule-based reasoning systems cannot be constructed. Moreover, a case-based reasoner can also use case-based reasoning as a heuristic. The system presented here, as most case-based reasoning systems, operates in a weak-theory domain. It differs from the systems presented above by the variety of the types of tasks it performs : analytic tasks such as diagnostic problem solving or treatment planning, and synthesis tasks such as concept learning. Concept learning is an assistance for clinical research, by facilitating the formulation of research hypotheses.

3 CASE-BASED REASONING TASKS

3.1 Analysis tasks

A task can be defined by an input space, a processing, often involving several steps, and a solutions' space. An analytic task is characterized by a limited solutions' space. Diagnoses for instance are solutions to the diagnostic problem, which are well-known by the clinician. Treatment planning, when the number of possibilities for each elementary treatment and for their combinations, is not too important, can be considered as an analytic task, as well as most problem-solving tasks. Furthermore case-based reasoning provides a means of transforming non analytic tasks into analytic tasks, by choosing among a set of previously solved cases, and of adaptation and combination heuristics.

Analytic tasks take advantage of the domain knowledge. When it is incomplete, ambiguous, or fastidious, case-based reasoning can perform such tasks advantageously.

3.2 Synthesis tasks

A synthesis task is a task the solutions' space of which is potentially unlimited. Most interpretive tasks, dealing with the interpretation of data, are synthesis tasks. In particular, clinical research is a synthesis task : among the numerous possible interpretations of clinical data, some must be chosen and studied. One of the aspects of clinical research this system focuses on is concept learning. Concept learning is a learning task that groups a set of empirical descriptions of instances in classes also called concepts [11]. Each concept has a particular characterization, generally expressed by a set of attributes, with numerical or symbolical values, and by relations between these attributes. Moreover, the concepts are organized in a hierarchy. More formally [12]:

1. Given: a set I of instances to be presented sequentially, and their descriptions d_i : I = { d_i };
2. Find: conceptual classes C_j that group those instances in categories ;
3. Find: an intentional definition for each category that characterizes the class D_j ;
4. Find a hierarchy H that organizes these classes.

An incremental concept learning system incorporates new instances one at a time to the concepts learnt from the previously processed instances. A good example of these systems is COBWEB [13]. It was then improved in CLASSIT [12].

Case-based systems, which are inherently incremental, are naturally adapted to this kind of concept learning. UNIMEM [3] is a case-based reasoning system for incremental concept learning. In the hierarchy it builds, each concept is linked to more general concepts by generalization links, and to less general ones by specialization links. New cases can be classified in several concepts at a time, giving that concepts can be added, modified or deleted after a time.

All the incremental concept learning systems presented so far are unsupervised. They don't take advantage of domain knowledge, either in knowledge bases, or in experts.

PROTOS [1], an exemplar-based classifier, is a supervised concept learning system. The main difference with the preceding systems is that it learns the categories it uses from the expert, and cannot learn new categories from the examples.

Nevertheless, PROTOS organization of cases and concepts are grounded on psychological research about concepts. For [14], concepts are organized around theories : only theories, and the structure they provide, can give concepts a cohesion, through explanations, possibly combining several levels of abstraction. Thus, the search for concepts cohesion is an important quality criterion for an incremental concept learning system.

3.3 Architecture

The reasoning process passes through several steps, which are the same for analysis and synthesis tasks :

1. The interpretation of the new case input data in order to determine potential indexes ;
2. The identification and retrieval of memorized cases, candidates to the processing of the new case : potential candidates are selected for their proximity to the new case, according to a certain *point of view*, filtering the significant description elements ;
3. The establishing of relations of correspondence between the potential candidates and the new case ; generally, these relations are quantified by a matching score, measuring the similarity between cases : this step leads to the selection of the best candidate, also called the best analogue ; it can be a memorized case or concept ;
4. The knowledge transfer from the best analogue to the new case, eventually including the adaptation of the memorized process of the best analogue ;

5. The explanation of the adaptation : it builds explanations from all the knowledge it possesses, that contained in the domain model, available from the beginning, and that in the indexed memory of cases ; this explanation process is detailed in [15] ;
6. The updating of the memory : if the modifications of the concepts are judged significant enough, the memory is updated, and the new case is stored under the modified concepts.

An important detail is that here, a candidate is a concept ; but it can also be a case if the match is closer. It then leads to the generation of a new concept.

In this system, the reasoning process is guided by a model of the domain, as in 2.2. Its role is to constrain the reasoning process whenever it is sensible, as can be seen on the schema of the architecture of the system (Figure 1).

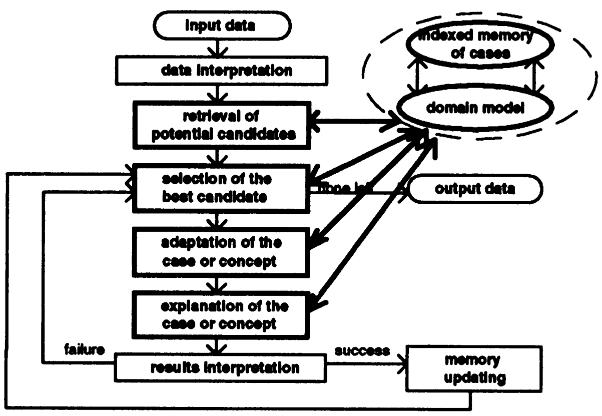

Figure 1. Schema of the architecture of the system.

The most important difference with a classical case-based reasoning system is in the adaptation step. The system adds to the regular adaptation step of case-based reasoning systems, an explanation step.

4 ORGANIZATION OF THE MEMORY

The organization of the memory is close to that of GBM [6]. Cases are sets of <attribute, value> pairs. Concepts are sets of quadruplets <attribute, value, positive counter, negative counter>. They are organized in a hierarchy, where the nodes are concepts. Each node is linked to the more general nodes above it in the hierarchy, and to the more specialized nodes under it, as well as cases directly indexed under it.

Each new case presented to the system entails, during the search through the memory, the updating of all concepts sharing enough <attribute, value> pairs with the new case. If the difference (positive counter - negative counter) goes down under a certain threshold (a parameter of the system), the corresponding attribute is withdrawn from the concept. If a concept has no attribute left, it is withdrawn. At the same time, if the new case shares enough <attribute, value> pairs with a concept, new generalizations, and new concepts, may be created. A generalization is constituted with all the common <attribute, value> pairs of the cases or concepts that are indexed under it. A concept is a generalization and the explanation generated for it. So, whenever a new case is processed, all related memorized concepts are updated, some eventually suppressed, and new concepts are sought for.

The organization of the memory has been improved, in particular for dealing with the problem of the dependence of concepts upon the order of presentation of instances. In this application, the small number of cases makes it compulsory to remedy for this situation. The search for the closest cases in memory, and for the concepts to which they belong, leads to the adaptation of the concept hierarchy so that the closest cases fall under the same concepts. This change permits to recover from hazardous concept formations.

Thus the classification obtained is dynamic, which meets an objective of ability to evolve. The threshold parameter permits to adapt the fineness of the classification. The usefulness of the classification is addressed by the model of the domain through the explanations provided for each concept : concepts are enriched with knowledge shared by all sub-concepts and cases depending on them. Besides, the explanation of the concepts also meets the objective of cohesion of the concepts.

So the memory is a dynamic memory containing both general concepts and specific cases.

5 PROTOTYPE EXAMPLE

5.1 Presentation

Psychiatry is a complex real-world domain, and a weak-theory one. In such domains, case-based reasoning is an advantageous AI methodology provided that cases are available [10]. In the eating-disorders' domain of psychiatry, the *Clinique des Maladies Mentales et de l'Encéphale* is a service active in clinical research, with well-documented patients' cases.

The aim of the system is to assist clinical expertise in the service, by learning thru experience [17]. The prototype presented in this section is applied to the study of the alimentary questionnaires of 61 in-patients. It proposes, for each new case presented to it, a diagnosis, a treatment plan, and at the same time, updates the concepts already in memory, thus serving clinical research.

5.2 Cases

The patients are 31 restrictive anorexics and 30 bulimic anorexics (according to the DSM-III-R criteria [16]). In this system, a case is a patient alimentary questionnaire, filled by the patient him or herself ; it is composed of a list of 232 foods, and 3 types of response per food :

1. The appreciation of the food by the patient, which can range between 3 values : "I appreciate it", "I'm indifferent to it" and "It disgusts me", respectively coded "1", "2" and "3" ;
2. The avoidance of the food by the patient, which can take the values "I avoid it", or "I don't avoid it", coded "0" and "1" ;
3. The reason of the possible avoidance of the food by the patient: it consists of one or two sentences hand-

written by the patient, such as "Too much fat.", "I don't eat meat.", "It makes me feel sick.". The reasons of avoidance are coded into 22 values ranging from "1" to "22" (in particular "9" means "fat", and "7" means "calories").

An example of a case is the following :

```
<Apricot-appreciation, 2>
<Apricot-avoidance, 1>
<Sausage-appreciation, 3>
<Sausage-avoidance, 0>
<Sausage-reason, 9>
<Banana-appreciation, 3>
<Banana-avoidance, 0>
<Banana-reason, 7> ...
```

The cases in memory are not all pathological. The case-base is composed of 61 patients' cases, and 36 control cases (see [5] for a discussion of the importance of the control case-base).

Another type of knowledge in memory is theoretical knowledge about foods. In this prototype, it represents the description of 572 foods, including alimentary category, composition in 35 elements such as water, mineral salts, vitamins ..., and aspect. The representation of a food takes the form <attribute, numerical value, qualitative value>, where qualitative value may take 5 values ranging from "very low" to "very high". For example, the food *low fat fish* is represented that way :

```
<calories, 112.0, very-low>
<water, 70.0, high>
<proteins, 24.0, very-high>
<plant-proteins, 0.0, very-low>
<animal-proteins, 24.0, very-high>
<glucides, 0.0, very-low> ...
```

5.3 Clinical problem-solving

The two clinical problems studied are diagnosis and treatment planning.

Here, the best analogue case serves as a model for solving the new case. Its diagnosis is proposed for the new case, and the treatment planning it had is also proposed for the new case. Concerning the alimentary questionnaires, the treatment planning is the list and sequence of the foods to be reintroduced. It is adapted to the new patient because not all the foods avoided are the same between the patients. Moreover, the order of reintroduction in the memorized case was elaborated with the patient after sometimes several hours of discussions with the clinicians. This order is a consensus between the patient and the clinicians, and is carefully prepared.

An example of this reasoning is the following :

```
The most similar patient in memory is
Ms MMM. This patient is a restrictive
anorexic, so I propose this diagnosis for
 the new patient Mrs XXX.

Important differences I have noted are
that the patient XXX appreciates more
kinds of meat (chicken and turkey) than
Ms MMM, which should make the treatment
less difficult.

The foods reintroduction I propose is:

1st week : salmon,
           veal,
           white rice
           orange.
2nd week : lamb,
           pasta,
           chocolate ...
```

5.4 Clinical research

Eating disorders are severe mental diseases, most of the time long-lasting, if not ever-lasting. The diagnosis is stated by simply matching the DSM-III-R criteria. A difficulty in diagnosis is that the diagnostic categories change over the life-time, and often several times, so that it is more exact to speak about the dominant symptomatology at a given time. This diagnostic instability leads to question the foundations of the diagnostic categories. Thus, it is an interesting subject to study the differences related to food choices, if any, between the diagnostic sub-groups.

The study must group the patients according to their answers to the questionnaire, in order to characterize the diagnostic sub-groups, to determine and characterize homogeneous sub-groups of patients within the diagnostic sub-groups, and to compare them to a control group of 36 non-pathological subjects considered as normal.

The results are summarized if Table 1 : the size of the input and output data is an indication of the performance of the system. The number of concepts learnt is limited, and shows a reasonable synthesis of the questionnaires.

Table 1. Performances of the concept learning.

	restrictive anorexics	bulimic anorexics	control subjects
Number of subjects	31	30	36
Number of concepts	52	55	30
Index size	2458	2528	1746

An example of a concept learnt, grouping 19 restrictive anorexics, is the following :

```
<prawn-appreciation, 1, 19, 2>
<tripes-appreciation, 3, 20, 1>
<potted-mince-appreciation, 3, 21, 2>
<dry-sausage-appreciation, 3, 21, 2>
<bacon-appreciation, 3, 22, 1>
<French-beans-appreciation, 1 , 28, 1>
<courgette-appreciation, 1, 30, 1>
<low-fat-fish-appreciation, 1, 31, 0>
<milk-chocolate-avoidance, 0, 25, 1>
<French-fries-avoidance, 0, 25, 1>
```

It is the eighth larger concept learnt from the restrictive anorexics with number of patients regrouped (19 of 31).

A short form of the explanations generated by the system contains the following elements :

```
The foods appreciated share :
   <calories, very-low>
   <water, high>
   <glucides, very-low>
   <lipids, very-low>
   <magnesium, very-high>
   <potassium, high>
   <lipids, very-low>
   <vitamin-B6, normal> ...

They are also appreciated by the control
subjects, in the same proportion for {French-
```

```
beans,courgette,low-fat-fish},   but   in   a
higher proportion (90%) for {prawn}.
They can be separated in 2 sub-groups, with:
group 1 = {prawn, low-fat-fish}
   <proteins, very-high>
   <sodium, high>
   <cholesterol, very-high>
   <phosphorus, very-high> ...
group 2 = {French-beans, courgette}
   <proteins, very-low>
   <sodium, very-low>
   <cholesterol, very-low>
   <phosphorus, very-low> ...
The foods in disgust share : ...
```

The content of the results is interesting for the application domain. It was found that the hierarchy constructed for the restrictive anorexics is very different from that of the bulimic anorexics, and that the two pathological hierarchies are very different from the control one. For instance, the simplest result is that the restrictive anorexics all appreciate and don't avoid low-fat fish, and only that food, and the system gave an explanation for this: low-fat fish is rich in animal proteins, and very poor in lipids and glucides : it is an optimized choice for a restrictive person. As for the bulimic anorexics, the food appreciated by 27 of them is melon, for which interesting explanations were proposed.

Subgroups were more complex, but it was found that the explanations given by the system permitted to characterize them in a meaningful way for the expert clinicians. The evaluation of the discrepancies and the similarities between the pathological subjects, and the control ones is an interesting measure of psychopathology.

6 CONCLUSION

The system presented here is a case-based assistant for clinical psychiatry expertise.

As recent case-based reasoning systems, it uses domain knowledge to guide the reasoning process. In a domain such as psychiatry, where empirical knowledge, by the study of control and patients' cases, is as important as theoretical knowledge, both types of knowledge are essential to the reasoning process.

The organization of the memory including two structures in close interrelationships, cases and concepts, gives the system a double ability : for problem-solving tasks, which are essentially analytic tasks, such as diagnosis and treatment planning, and for interpretative tasks, which are essentially synthetic tasks, such as assisting the formulation of hypotheses for clinical research.

The prototype presented is currently enriched with the numerous other data collected from the patients : biological, behavioural, psychological and anamnestic, and comparisons with other formalization methodologies, statistical or data analytic, traditionally used in the domain, is also a present topic of research.

Acknowledgments

I would like to thank professor Samuel-Lajeunesse, doctor Mirabel-Sarron (M.D.) and Magali Volery (dietician) for sharing ideas and work in eating disorders research.

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